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A Transform-Domain Approach to Super-resolution Mosaicing of Compressed Images

Mark Pickering, Getian Ye, Michael Frater and John Arnold
School of Information Technology and Electrical Engineering
University College, The University of New South Wales
Australian Defence Force Academy, Australia
E-mail: m.pickering@adfa.edu.au

Abstract. The combination of image mosaicing and super-resolution imaging, i.e. super-resolution mosaicing, is a powerful means of representing all the information of multiple overlapping images to obtain a high resolution broad view of a scene. In most current image acquisition systems, images are routinely compressed prior to transmission and storage. In this paper, we present a robust super-resolution mosaicing algorithm which can be applied to compressed images. The algorithm operates on the quantized transform coefficients available in the compressed bitstream so that super-resolution reconstruction can be implemented directly in the transform domain. In order to improve the performance of super-resolution mosaicing, an adaptive approach to determining a regularization parameter is proposed. It is shown that this algorithm is robust against outliers and provides reconstructed super-resolution images with improved quality.

1. Introduction
In recent years, super-resolution (SR) or high-resolution (HR) image reconstruction has been an active research area. SR image reconstruction algorithms investigate the relative subpixel motion information between multiple low-resolution (LR) images and increase the spatial resolution by fusing them into a single frame. Therefore, they can overcome the inherent resolution limitation of the LR imaging system. The basic premise for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured of the same scene. In SR, typically, the LR images represent different views of the same scene. If the LR images are shifted by integer units, then each image contains the same information, and thus there is no new information that can be used to reconstruct an SR image. If the LR images have different subpixel shifts from each other, the new information contained in each LR image can be exploited to obtain an SR image.

There exist many different methods for SR image reconstruction [1, 2]. The main purpose of these methods is to improve the resolution of a single image using other images from an image sequence. SR reconstruction techniques have also been combined with image mosaicing to generate SR mosaics with improved resolution. Zomet et. al. presented a method that is the combination of manifold mosaicing and SR reconstruction [3]. In this method, the SR reconstruction technique proposed in [4] is applied to a strip rather than an image, i.e., the resolution of each strip in the mosaic is enhanced by using all the LR images that contain that strip. Hence, this method requires a strip collection process. However, The SR processing for
each strip is computationally expensive. In [5], an SR mosaicing method based on image warping was proposed. In this method, each pixel of each frame is mapped into the SR mosaic and its gray-level value is assigned to the corresponding pixel in the SR mosaic if it falls close to an integer-pixel position (e.g., \(\pm 0.2\) pixel units) in the SR mosaic. The remaining empty pixel positions are filled using bilinear interpolation. Although this method is simple, it has some drawbacks: (1) a pixel in the SR mosaic may be assigned more than once when the pixels from different LR images satisfy the same threshold; and (2) the bilinear interpolation, which is used to fill the remaining holes, may not be optimal for SR reconstruction. Both methods presented in [3] and [5] are not robust to the outliers that result from motion errors, moving objects, inaccurate segmentation, etc. Additionally, they do not consider reconstructing SR images from the SR mosaic, which will also have improved visual quality.

In most current image acquisition systems, images are routinely compressed prior to digital transmission and storage. Hence, some attention has recently been directed to SR reconstruction of compressed video or image sequences. The well-known JPEG and MPEG compression systems, which are block-based encoders, introduce a variety of coding errors such as blocking artifacts and ringing artifacts. A number of image restoration techniques have been proposed to attenuate compression artifacts (e.g., [6, 7, 8]). Various combinations of these post-processing techniques with traditional SR reconstruction methods have been proposed by Segall et al. in [9, 10]. In these algorithms a stochastic regularization approach is adopted utilizing maximum a posteriori (MAP) methods while in the algorithm presented in this paper a deterministic approach is adopted using a constrained least squares (CLS) framework. B. Gunturk et al. [11] proposed a Bayesian SR reconstruction technique that uses statistical information about quantization noise directly in the compressed domain. In [12], a method that simultaneously estimates the quantization noise along with the SR image was proposed for compressed images.

In this paper, we propose a robust SR mosaicing algorithm for compressed images. Firstly, an observation model is presented to describe the relationship between the SR mosaic image and the observed LR images. Then, by incorporating the image compression process into the observation model, we propose a spatial-domain and a transform-domain SR mosaicing algorithm for compressed images. The spatial-domain algorithm is an extension of that for uncompressed images. The transform-domain algorithm exploits the quantized transform coefficients, which are available in the compressed bit-stream, so that the SR reconstruction can be implemented directly in the transform domain.

The remainder of this paper consists of four sections. In Section 2, an observation model for uncompressed images is defined and a robust SR mosaicing algorithm is described for uncompressed images. The adaptive determination of the regularization parameter and the implementation of the proposed algorithm are discussed. In section 3 the SR mosaicing algorithm is then extended to encompass compressed images. An observation model that considers the compression process is presented and spatial-domain and transform-domain algorithms are proposed for compressed images. The efficacy of these algorithms are illustrated through experiments in 4. Finally, conclusions are drawn in Section 5.

2. SR Mosaicing of Uncompressed Images

2.1. Observation model

Theoretic and practical limitations usually constrain the achievable resolution of any imaging device. As illustrated in Fig. 1, a real scene is seen to be warped at the camera lens due to the relative motion between the scene and camera. The images are often degraded by both optical blur and motion blur. They are then discretized or downsampled resulting in a digitized, blurred, and noisy LR image. Based on the image formation model, the objective of SR mosaicing is to solve the inverse problem, i.e., determine the SR mosaic image from the observed LR images.

Assuming that there are \(K\) frames of LR images available, the observation model can be
Figure 1. The observation model relating the observed LR images to the real SR image.

represented as

\[ y_k = DB_k W_k R [x]_k + n_k = H_k x + n_k, \]

where \( y_k \) \((k = 1, 2, \ldots, K)\), \( x \), and \( n_k \) denote respectively the \( k \)th LR image, the part of the real world scene depicted by the SR mosaic, and the additive noise, which are rearranged in lexicographic order. The observation model in (1) introduces \( R [\cdot]_k \), which represents the reconstruction of the \( k \)th warped SR image from \( x \). The inverse of this reconstruction operator plays a significant role in the SR mosaic building process as it defines how each SR image is blended into the final SR mosaic. The geometric warp operator and the blur matrix between \( x \) and the \( k \)th LR image \( y_k \) are represented by \( W_k \) and \( B_k \), respectively. The decimation operator is denoted by \( D \).

2.2. Robust SR mosaicing

The estimation of an unknown SR mosaic image is not exclusively based on the observed LR images. It is also based on many assumptions such as the motion model, blurring process, and noise. In this paper, the projective model [13] is used to describe the relative motion or geometric transformation between the observed LR images. Only optical blur is considered, which is assumed to be linear and spatially invariant. The additive noise \( n_k \) in (1) is assumed to be independent and identically distributed white Gaussian noise. With this noise model, the problem of finding the maximum likelihood estimate of the SR mosaic image \( \hat{x} \) can be formulated as

\[
\hat{x} = \arg \min_x \left\{ \sum_{k=1}^{K} \| y_k - DB_k W_k R [x]_k \|_2^2 \right\},
\]

where \( \| \cdot \|_2 \) denotes the 2-norm.

Determining the SR reconstruction is often an ill-posed problem [1] because of an insufficient number of LR images and an ill-conditioned blur operator. Procedures adopted to stabilize the inversion of ill-posed problem are called regularization. It is helpful to find a stable solution and improve the rate of convergence [14]. By using a deterministic regularization, the constrained
least squares (CLS) formulation can be written as [1]

\[
\hat{x} = \arg \min_x \left\{ \sum_{k=1}^K \| y_k - DB_k W_k R[k] \|_2^2 + \lambda \|Lx\|_2^2 \right\}, \tag{3}
\]

where \( L \) is chosen to be the 2-D Laplacian operator that is commonly used in image restoration and SR reconstruction. In (3), \( \lambda \) is the regularization parameter that controls the tradeoff between fidelity to the original data and smoothness of the solution. To be specific, a large value of \( \lambda \) often leads to a smoother solution. This is useful when only a small number of LR images are available or the fidelity of the observed data is low due to registration error and noise. On the other hand, if a large number of LR images are available and the amount of noise is small, a small value of \( \lambda \) leads to a good solution [16, 17].

Based on the gradient descent algorithm for minimizing (3), the robust iterative update for \( \hat{x} \) can be expressed as

\[
\hat{x}^{(n+1)} = \hat{x}^{(n)} + \alpha^{(n)} \left\{ \mathbf{R}^T \left[ \mathbf{W}_k^T \mathbf{B}_k^T \mathbf{D}_k^T (y_k - DB_k W_k R[k]) \right]_{k=1}^K - \mathbf{L}^{(n)} \mathbf{R}^{(n)} \right\}, \tag{4}
\]

where \( \alpha^{(n)} \) is a scalar defining the step size in the direction of the gradient and \( \mathbf{D}_k^T \) denotes the interpolation operator. In (4), \( \mathbf{R}^T \left[ \right]_{k=1}^K \) represents the mosaic construction using \( K \) frames of images. Temporal median filtering is adopted for image blending because it is robust to outliers caused by independent moving objects and shadows. Moreover, it often results in a sharper mosaic image by comparison with temporal averaging or weighted temporal averaging. Median filtering is implemented for simplicity however other robustness algorithms such as the method proposed by Zomet [18] or the bilateral total variation (TV) approach proposed by Farsiu [14] could be included to improve the performance of the algorithm at the cost of higher complexity. As seen from (4), an error mosaic is built by using all the errors or differences between the original and reconstructed LR images. This error mosaic image is subsequently used for updating the SR mosaic. This process is repeated iteratively to minimize the energy of the error in (3). Since temporal median filtering is used for blending both the initial mosaic \( \hat{x}^{(0)} \) and error mosaic images, large projection errors caused by outliers will have a small influence on the SR mosaic. A brief description of the proposed algorithm is illustrated in Fig. 2.

The critical issue in the application of (4) is the determination of the regularization parameter \( \lambda^{(n)} \), which balances the constraint \( \| L \hat{x} \|_2^2 \) and the error energy \( \| y_k - H_k \hat{x} \|_2^2 \). In [17], the
properties that the regularization parameter should satisfy were investigated and an approach to the general choice of the regularization parameter was proposed for image restoration. According to the analysis in [17, 19], we define the regularization parameter $\lambda^{(n)}$ as

$$
\lambda^{(n)} = \left( \frac{\sum_{k=1}^{K} ||y_k - DB_k W_k R[x^{(n)}]_k||_2}{K \|L\hat{x}^{(n)}\|_2} \right)^2.
$$

(5)

The numerator of the right term in (5) is the error energy, which decreases with the iteration. That is, the differences between the reconstructed LR images and observed LR images become smaller as the iteration proceeds. The rate of change of the regularization parameter becomes smaller as the error energy decreases. The denominator of the right term in (5) is the energy of the high-pass filtered SR mosaic image i.e., $\|L\hat{x}^{(n)}\|_2^2$. With the progress of the iterative process, the value of $\|L\hat{x}^{(n)}\|_2^2$ increases because high frequency components in $\hat{x}^{(n)}$ are restored. Thus, the value of the regularization parameter decreases with the iteration.

It is noted that most image mosaicing techniques only consider using non-interlaced image sequences. In fact, the mosaicing techniques can be applied to interlaced sequences as well. In this case, we treat the top and bottom fields in the same frame as different images. The image registration is performed between the reference field and all other fields and both fields are then blended into a mosaic using the estimates of the motion parameters. Therefore, the proposed SR mosaicing algorithm is naturally applicable to interlaced image sequences.

3. SR Mosaicing of Compressed Images

3.1. Observation model

In this section, we incorporate the image compression process into the observation model defined in (1) and propose SR mosaicing algorithms for compressed images. We use a block-based JPEG encoder that utilizes the discrete cosine transform (DCT).

It is assumed that there are $K$ frames of LR images available. These images are then compressed before transmission and storage. In common JPEG compression, each LR image is divided into equally sized blocks that are processed independently with the forward block-based DCT. The resulting DCT coefficients are quantized and the quantized coefficients are subsequently represented with an efficient lossless code. At the decoder, an estimate of the original image is generated by calculating the inverse block-based DCT of the quantized DCT coefficients that are available in the compressed bit-stream. Considering the compression process and following the model (1) presented in Section 2.1, the conversion of the SR mosaic image $x$ to the $k$th compressed LR image $\tilde{y}_k$ can be expressed as

$$
\tilde{y}_k = T^T Q^T Q^T T y_k = T^T Q^T Q^T T(H_k x + n_k),
$$

(6)

where $T$ and $T^T$ represent the forward and inverse block-based DCT, respectively, and $T^T = T^{-1}$. The quantization and de-quantization operators are denoted by $Q$ and $Q^T$, respectively. Defining $z_k$ as the quantized DCT coefficients, the relationship between the SR mosaic image $x$ and the quantized DCT coefficients $z_k$ can be represented as

$$
z_k = Q^T y_k = Q^T(H_k x + n_k) = QTH_k x + \tilde{n}_k,
$$

(7)

where $\tilde{n}_k$ denotes the additive noise in the transform domain.

We now consider the effect of the quantization operator that is a lossy procedure. The quantization is typically realized by dividing each transform coefficient by a quantization scale factor and then rounding the result to the nearest integer. During the image compression
process, quantization noise is introduced. If we define $n^Q$ as the quantization noise in the transform domain, (6) can be rewritten as [9, 1]

$$\hat{y}_k = T^T (TH_k x + Tn_k + \bar{n}_k^Q) = H_k x + n_k + n^Q_k,$$

(8)

where $n^Q_k = T^T \bar{n}_k^Q$ represents the quantization noise in the spatial domain. The quantization operator quantizes each DCT coefficient independently and hence the quantization noise is not correlated in the transform domain. Moreover, the DCT operator is linear. Therefore, the quantization noise in the spatial domain becomes a linear combination of independent noise processes. By the Central Limit Theorem, the distribution of the quantization noise in the spatial domain tends to be Gaussian [9, 12]. Because the additive noise $n_k$ and the quantization noise $n^Q_k$ have independent Gaussian distributions, the overall noise $e_k = n_k + n^Q_k$ is also a Gaussian distribution.

### 3.2. Robust SR mosaicing for compressed images

#### 3.2.1. Spatial-domain algorithm

According to the discussion in Section 3.1, if the quantization noise in the spatial domain is assumed to be white Gaussian noise and the observation model in (8) is adopted, a CLS formulation similar to (3) can be obtained. That is,

$$\hat{x} = \arg \min_x \left\{ \sum_{k=1}^K \| y_k - DB_k W_k R[x]_k \|_2^2 + \lambda \| Lx \|_2^2 \right\} .$$

(9)

Likewise, the robust iterative update for $\hat{x}$ can be expressed as

$$\hat{x}^{(n+1)} = \hat{x}^{(n)} + \alpha^{(n)} \left\{ R^T \left[ W_k^T B_k D^T (\hat{y}_k - DB_k W_k R[\hat{x}^{(n)}]_k) \right]_{k=1}^K - \lambda^{(n)} L^T L \hat{x}^{(n)} \right\} .$$

(10)

We can see that the spatial-domain algorithm described above is a straightforward extension of the algorithm presented in Section 2.2. Thus, the regularization parameter $\lambda^{(n)}$ in (10) can be determined as

$$\lambda^{(n)} = \left( \frac{\sum_{k=1}^K \| y_k - DB_k W_k R[x^{(n)}]_k \|_2}{K \| Lx^{(n)} \|_2} \right)^2 .$$

(11)

The proposed spatial-domain algorithm is based on the assumption that the quantization noise in the spatial domain is white Gaussian noise. At high compression ratios, however, the quantization noise depends on both the original signal and the quantization parameters. The quantization noise in the spatial domain is in general correlated and spatially varying [20]. Therefore, modeling the quantization noise in the spatial domain as white Gaussian noise may not be sufficient. An alternative approach is to minimize the error between the original LR transform coefficients and the reconstructed transform coefficients as the quantization noise associated with the original LR transform coefficients can be better approximated as white Gaussian noise.

#### 3.2.2. Transform-domain algorithm

In JPEG compression, the quantized DCT coefficients and the corresponding quantization table are available at the decoder. If the additive noise in the transform domain is assumed to be white Gaussian noise and the model in (7) is adopted, a CLS formulation in the transform domain can be obtained. That is,

$$\hat{x} = \arg \min_x \left\{ \sum_{k=1}^K \| z_k - QTDB_k W_k R[x]_k \|_2^2 + \lambda \| Lx \|_2^2 \right\} .$$

(12)
In order to minimize (12), a robust iterative update for $\hat{x}$ can be expressed as

$$\hat{x}^{(n+1)} = \hat{x}^{(n)} + \alpha^{(n)} \left\{ R^T \left[ W_k^T B_k^T D^T T^T Q^T (z_k - QTDB_k R[\hat{x}^{(n)}]) \right] K \sum_{k=1}^{K} - \lambda^{(n)} L^T L \hat{x}^{(n)} \right\}. \quad (13)$$

It is seen from (13) that the transform-domain algorithm utilizes all the errors or differences between the original and reconstructed quantized DCT coefficients. These errors are inverse quantized and transformed by the inverse block-DCT. The resulting error images are then interpolated and blended into an error mosaic that is subsequently used for updating the SR mosaic image $\hat{x}^{(n)}$. The regularization parameter $\lambda^{(n)}$ in (12) is employed to balance the constraint $\|Lx\|_2^2$ and the error energy $\|z_k - QTDB_k W_k R[\hat{x}^{(n)}]\|_2^2$. Thus, we define $\lambda^{(n)}$ as

$$\lambda^{(n)} = \left( \frac{\sum_{k=1}^{K} \|z_k - QTDB_k W_k R[\hat{x}^{(n)}]\|_2^2}{K \|L\hat{x}^{(n)}\|_2^2} \right)^2. \quad (14)$$

### 3.3. Implementation

Although the matrix-vector notation provides a neat formulation, the implementation of the proposed algorithm with images converted into vectors is problematic, especially when dealing with large images. Hence, in practice, the proposed algorithm is implemented using simple image operations such as warping, convolution, interpolation, and decimation. These operations are described as follows:

- **R** and **R**: $R$ represents the reconstruction from a mosaic image and is implemented by choosing the corresponding portion of the mosaic content based on the projective motion parameter. $R^T$ represents the construction of a mosaic. It is implemented by coordinate projection and image blending, which is based on temporal median filtering.

- **W** and **W**: If $W$ is implemented by backward warping, $W^T$ should be the forward warping by the inverse motion. Bilinear interpolation is utilized in image warping.

- **B** and **B**: $B$ is implemented by convolution with the PSF kernel. $B^T$ is implemented by convolution with the flipped PSF kernel, i.e., if $h(i, j)$ denotes the PSF kernel, the flipped PSF kernel is then $h(-i, -j)$.

- **D** and **D**: $D$ and $D^T$ are implemented by image interpolation and decimation, respectively. Image interpolation refers to the process of upsampling followed by appropriate low-pass filtering, while image decimation refers to downsampling after appropriate anti-alias filtering (see Fig. 3). We only consider image interpolation and decimation by an integer factor (e.g., by 2). In this paper, the low-pass synthesis and analysis filters of biorthogonal spline wavelets are used as low-pass and anti-alias filters for image interpolation and decimation, respectively. There are two main advantages of using these filters: First, they satisfy the
perfect reconstruction condition, i.e., \( |H(z)G(z)|_2 = 1 \) [21], where \( H(z) \) and \( G(z) \) denote the low-pass and anti-alias filters, respectively. This is very important when reconstructed images from the SR mosaic are required (e.g., in sprite coding [13]). Secondly, it is found that the low-pass synthesis filter achieves better results for image interpolation than other conventional techniques such as bilinear and bicubic filters. We choose low-pass analysis and synthesis filters of the biorthogonal Daubechies 7/9 wavelet transform [22] because they are commonly used in image processing and coding applications. The low-pass filters of other biorthogonal spline wavelets can also be used provided that they are of sufficient length.

- \( \mathbf{L} \) and \( \mathbf{L}^T \): The implementation of \( \mathbf{L} \) and \( \mathbf{L}^T \) in the spatial domain is similar to that of the blur operators. The convolution kernel corresponding to the Laplacian operator is defined as [15]:

\[
\frac{1}{4} \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}.
\]  

4. Experimental Results
Assessing the performance of an SR algorithm is not easy because the solution quality depends on several tasks, which include image registration, interpolation, and restoration. In this section, we present some experiments to evaluate the proposed SR mosaicing algorithm using some synthetic and real images. These experiments are divided into two parts: SR mosaicing for synthetic images and SR mosaicing for real images. In order to measure the performance of the proposed algorithm quantitatively, the peak signal to noise ratio (PSNR) is calculated. It is defined by

\[
\text{PSNR} = 10 \log_{10} \frac{255^2 N}{\| \mathbf{x} - \hat{\mathbf{x}} \|^2},
\]

where \( N \) is the total number of pixels and \( \mathbf{x} \) and \( \hat{\mathbf{x}} \) are the original image and the impaired image, respectively. When using the proposed SR mosaicing algorithm, the iterative procedure is terminated using the following criterion

\[
\left\| \mathbf{x}^{(n+1)} - \mathbf{x}^{(n)} \right\|^2_2 / \left\| \mathbf{x}^{(n)} \right\|^2_2 \leq 10^{-6}.
\]

In addition, \( \alpha^{(n)} \) and the number of iterations are chosen to be 1 and 10, respectively.

4.1. Synthetic experiment
A synthetic experiment was conducted using a sequence of synthetically generated LR images. The synthetic image sequence was created by using the central 400 \times 400 pixel region of the \( \text{Boat} \) image. The image was shifted by an integer pixel amount in both the horizontal and vertical directions. This shifted image was then convolved with the following filter kernel:

\[
\frac{1}{256} \begin{bmatrix} 26 & 30 & 26 \\ 30 & 32 & 30 \\ 26 & 30 & 26 \end{bmatrix}.
\]  

The resulting image was downsampled by two horizontally and vertically. The same approach with different shifts in the horizontal and vertical directions was used to produce 10 frames of LR images from the original \( \text{Boat} \) image. The size of each LR image was 200 \times 200 pixels.

The LR images were compressed with a JPEG codec to generate compressed LR images. In JPEG compression, the quality factor, which ranges from 1 (worst quality) to 100 (best
quality), was selected to be 60. When using the transform-domain algorithm, the quantized DCT coefficients and the corresponding quantization table were obtained from the compressed bit-stream. For comparison purposes, an LR mosaic is also constructed for the synthetic LR image sequence.

To subjectively compare the LR mosaic and SR mosaics obtained from the spatial-domain and transform-domain algorithms, detailed regions of each mosaic were extracted and these regions are illustrated in Fig. 4 and Fig. 5 (a) and (b) respectively. Fig. 4 and Fig. 5 clearly show that both the spatial-domain and transform-domain algorithms can produce SR mosaics with improved resolution. Fig. 5 also shows that the subjective quality of the transform-domain algorithm is superior to that of the spatial-domain algorithm. Fig. 6 (a) and (b) show the convergence plots of the proposed algorithms and the regularization parameter $\lambda^{(n)}$ versus the number of iterations, respectively. Fig. 6 shows that the proposed algorithm converges to an estimate of the SR mosaic image and the regularization parameter decreases as the error energy decreases.

![Figure 4. Detailed region cropped from the LR mosaic image.](image)

Now consider the reconstruction of SR images from the SR mosaics. As the original synthetic SR images were available, PSNR values can be computed. The reconstructed SR images were also compared with the interpolated, compressed LR images obtained from bilinear, bicubic, and wavelet-based interpolation methods. The performance of the proposed algorithms were evaluated for different JPEG quality factors and a comparison of the average PSNR values for the five different methods is given in Table 1. It can be seen that the proposed algorithms perform better than other interpolation methods. Moreover, the transform-domain algorithm outperforms the spatial-domain algorithm for all quality factors.

4.2. Nonsynthetic experiment
In this experiment, a part of the background in the **Mobile & Calendar** sequence was used to generate an LR image sequence. The images used here differ from those used in the synthetic
Figure 5. (a)(b) Detailed regions cropped from SR mosaic images produced by the spatial-domain and transform-domain respectively.
Figure 6. (a) The convergence plots for the synthetic experiment in Section 4; (b) The regularization parameter $\lambda^{(n)}$ versus the number of iterations.
Table 1. PSNR comparison of different methods for the synthetic experiment in Section 4.1.

<table>
<thead>
<tr>
<th>JPEG quality factor</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80</th>
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<tr>
<td>Bilinear</td>
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<td>25.76</td>
<td>25.88</td>
<td>26.00</td>
</tr>
<tr>
<td>Bicubic</td>
<td>25.79</td>
<td>25.93</td>
<td>26.08</td>
<td>26.24</td>
</tr>
<tr>
<td>Wavelet</td>
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<td>27.90</td>
<td>28.29</td>
<td>28.73</td>
</tr>
<tr>
<td>Spatial-domain</td>
<td>27.70</td>
<td>28.28</td>
<td>29.08</td>
<td>29.95</td>
</tr>
<tr>
<td>Transform-domain</td>
<td>29.45</td>
<td>29.84</td>
<td>30.34</td>
<td>30.85</td>
</tr>
</tbody>
</table>

The experiment in two important ways: First, the subpixel motions between images are no longer defined explicitly. The motion now corresponds to inherent motion within the scene introduced by the camera and object. Secondly, all pixels in the SR image may not appear throughout the LR images, i.e., a pixel may not be observable or may only be observable in temporally distinct observations. As the Mobile & Calendar sequence is an interlaced sequence, the top and bottom fields in the same frame are treated as different images. 50 frames of images of size 352 × 176 pixels, i.e., 100 fields of size 176 × 176 pixels were used. The 25th top field was chosen to be the reference field for image registration and mosaicing. Because the PSF of the imaging system was unknown, the PSF kernel was selected to be 1. The LR images were then compressed using a JPEG codec with the quality factor selected to be 60.

Figure 7. Detailed region cropped from the LR mosaic image.

To subjectively compare the LR mosaic and SR mosaics obtained from the spatial-domain and transform-domain algorithms, detailed regions of each mosaic were extracted and these regions are illustrated in Fig. 7 and Fig. 8 (a) and (b) respectively. Fig. 7 and Fig. 8 clearly show that both the spatial-domain and transform-domain algorithms can produce SR mosaics with improved resolution. Fig. 8 also shows that the subjective quality of the transform-domain algorithm is superior to that of the spatial-domain algorithm.
Figure 8. (a)(b) Detailed regions cropped from SR mosaic images produced by the spatial-domain and transform-domain respectively.
Now consider the reconstruction of SR images from the SR mosaics obtained from the proposed spatial-domain and transform-domain algorithms. The reconstructed SR images are compared with the interpolated LR images obtained from the bilinear, bicubic, and wavelet-based interpolation methods. As the original SR images are not available, it is only possible to compare the visual quality of the reconstructed SR images.

Detailed regions cropped from SR images obtained using these five techniques are shown in Fig. 9. It is clear from Fig. 9 that the proposed algorithms perform better than other interpolation methods as these methods are simply interpolating the blocking artifacts caused by the image compression process. Moreover, the transform-domain algorithm outperforms the spatial-domain algorithm.

5. Conclusions

In this paper, we have proposed SR mosaicing algorithms for uncompressed and compressed images. We firstly introduced an observation model to describe the relationship between the SR mosaic image and the observed LR images. Based on this model, a robust SR mosaicing algorithm was proposed for uncompressed images. The implementation of this algorithm, which includes wavelet-based interpolation and decimation and adaptive determination of the regularization parameter, has been presented. By incorporating the image compression process into the observation model, we then proposed SR mosaicing algorithms for compressed images, i.e., the spatial-domain and transform-domain algorithms. The spatial-domain algorithm is based on the assumption that the quantization noise in the spatial domain is white Gaussian noise which may not be valid at high compression ratios. The transform-domain algorithm exploits the quantized transform coefficients so that the SR mosaicing is implemented directly in the transform domain. Some synthetic and nonsynthetic experiments have been conducted to explore the efficacy of the proposed algorithms. Experimental results showed that the proposed algorithms can not only provide an SR mosaic but also provide reconstructed SR images with improved quality. In addition, when handling the compressed images, the spatial-domain and transform-domain algorithms can attenuate blocking artifacts caused by image compression. Furthermore, the transform-domain algorithm outperforms the spatial-domain algorithm.

6. References

Figure 9. Detailed regions cropped from the reconstructed SR images obtained from (a) Bilinear interpolation; (b) Bicubic interpolation; (c) Wavelet-based interpolation; (d)(e) The SR mosaics obtained from the proposed spatial-domain and transform-domain algorithms, respectively.